A NEURAL SOLUTION FOR MULTITARGET TRACKING BASED ON A MAXIMUM LIKELIHOOD APPROACH

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ABSTRACT

This paper presents a new neural solution for multitarget tracking based on a maximum likelihood approach. In the radar tracking context, neural networks are generally used to decide which plot can be assigned to each predetected track, in taking into account only the plots received during the last scan. A neural approach is proposed to determine which particular combinations of the plots received during the k latest scans are likely to represent true target tracks. This data association problem is viewed as a multiple hypothesis test that can be solved in maximizing a likelihood function by means of an Hopfield neural network. Some simulation results are presented to illustrate the behaviour of the proposed neural tracking solution.

1. INTRODUCTION

The multitarget tracking problem consists in detecting the objects situated in the observation space and estimating their trajectory. During each scan, a radar sensor delivers a set of measurements, called plots. Each object of the observation space doesn't generate an echo everytime due to non-detections, and each plot isn't associated with a target everytime due to false alarms.

Several approaches have been proposed in the literature to solve the tracking problem in using neural networks: in [1, 2, 3] an Hopfield model decides which plot to assign to each predetected track, by minimizing the sum of the plot-to-track distances. Schmidlin [4], and Winter [5] proposed neural methods to minimize a new assignment criterion. In [6, 7] the neural architecture is the same, but the decisions are made so that the likelihood of each association is optimized. All these approaches consider only plots received during the last scan; the optimization process then reduces to the well known assignment problem. For sufficiently small size problems (number of tracks less than 50), it can be solved by an optimal method like the Munkres algorithm [8] in a reasonable computional time, so that the use of neural networks is not justified in these cases.

In this paper, the tracking problem is tackled from a more general point of view, as a partitioning of the plots received during k scans, into sets of tracks and sets of false alarms. The solution is obtained by maximizing the likelihood of the hypotheses relating to this partitioning. The corresponding assignment problem is NP-complete. Thus, the optimal solution can not be reached in an acceptable calculation time, and the use of neural networks, which fastly converge to near optimal solutions, is of a great interest in this case.

In the next section, we describe the likelihood function to be optimized. This likelihood is derived fom models introduced by Sittler [9] Morefield [10] and Blackman [11]. Section 3 proposes a solution to maximize the likelihood function by means of an Hopfield neural network. Some simulation results are presented in section 4 and concluding remarks are made in section 5.

2. THE LIKELIHOOD FUNCTION

To determine the likelihood function associated with a partitioning of the observations received during k scans, into sets of tracks and false alarms, several models have to be first defined. Assuming that new targets randomly arise within the scan volume V, with a density β_N, the probability P_N that n_N new targets appear in n_N small cells of volume v, during the k latest scans, can be modeled by [12]:

$$P_N(n_{N_k}) = (\beta_N v)^{n_{N_k}} \, e^{-\beta_N kV} \tag{1}$$

Similarly, the probability P_F that exactly n_{F_k} false alarms arise is:

$$P_F(n_{F_k}) = (\beta_F v)^{n_{F_k}} \, e^{-\beta_F kV} \tag{2}$$

where β_F is the density of false alarms. Given that a true target was detected, the conditional track length probability also need to be modelized. The following expression was first introduced by Sittler [9] in the ship tracking context, and derived by Blackman [11] for a general purpose. Two cases must be distinguished:

- if track i is still present at scan k, the probability that it ends with a length greater than TL_i is given by:

  $$P_{TL_k}(TL_i) = e^{-\left(\frac{TL_i}{EL}\right)} \tag{3}$$

  where EL is the expected track length in scans.

- if track i terminated with length TL_i:

  $$P_{TL_k}(TL_i) = \left(1 - e^{-\left(\frac{1}{EL}\right)}\right) e^{-\left(\frac{TL_i}{EL}\right)} \tag{4}$$

The probability P_{DS_i} of a particular sequence of detection for the track i with length TL_i is as follows:

$$P_{DS_i} = P_d^{NU_i} (1 - P_d)^{TL_i - NU_i} \tag{5}$$

where NU_i is the number of updates for track i, *i.e.* the number of plots affected to track i after initial detection, and Pd is the probability of detection. For each plot assignment to a track, the likelihood is linked to the prediction error statistics. Thus, the probability of the track i having NU_i residual errors within NU_i cells of volume v is:

$$P_{AS_i} = v^{NU_i} \prod_{j=1}^{NU_i} f_i(\nu_{ij}) \tag{6}$$

where $f_i(\nu_{ij})$ is the probability density of the residual ν_{ij} for the j-th observation of the track i, at scan k.With the Gaussian assumption, $f_i(\nu_{ij})$ is given by:

$$f_i(\nu_{ij}) = \frac{1}{(2\pi)^{M/2}\sqrt{\mid C_i \mid}} e^{-\frac{\nu_{ij}^t C_i^{-1} \nu_{ij}}{2}} \tag{7}$$

where $\mid C_i \mid$ is the determinant of the residual covariance matrix C_i associated with track i, and M is the measurement dimension. According to [11], combining equations (1) to (7) leads to define the following composite probability L_k associated with any particular observation partitioning hypothesis given k scans:

$$\begin{aligned} L_k &= P_N(n_{N_k}) P_F(n_{F_k}) \\ & \prod_{i=1}^{TN} \left[P_{TL_k}(TL_i)\, P_{DS_i} \prod_{j=1}^{NU_i} P_{AS_i} \right] \quad (8) \\ &= A \beta_N^{n_{N_k}} \beta_F^{n_{N_k}} \prod_{i=1}^{TN} \left[P_{TL_k}(TL_i)\, P_{DS_i} \prod_{j=1}^{NU_i} f_i(\nu_{ij}) \right] \quad (9) \end{aligned}$$

where TN is the number of tracks that satisfy the constraint that at most one track is associated to each plot, and:

$$A = v^{NP} e^{-k(\beta_N + \beta_F)V} \tag{10}$$

with:

$$NP = n_{N_k} + n_{F_k} + \sum_{i=1}^{TN} NU_i \tag{11}$$

We can notice that NP is a constant, and equals the total number of plots received during the k latest scans, so that A is a constant factor. The search for the partitioning that maximizes L_k leads to a NP-complete problem. In real-time applications, the search for the optimal solution may be too time consuming. This is the reason why neural networks represent an interesting alternative. They do not guarantee to provide the optimal solution but they generally converge to a near optimal solution, in a reasonable computation time. Such a solution is developed in the next section.

3. NEURAL OPTIMIZATION

Using equation (11), the expression (9) of the likelihhod function L_k can be rewritten as follows:

$$\begin{aligned} L_k &= A \beta_F^{n_{NP}} \prod_{i=1}^{TN} \left[\frac{\beta_N}{\beta_F} P_{TL_k}(TL_i)\, P_{DS_i} \prod_{j=1}^{NU_i} \frac{f_i(\nu_{ij})}{\beta_F} \right] \quad (12) \\ &= A \beta_F^{n_{NP}} \prod_{i=1}^{TN} q_i \quad (13) \end{aligned}$$

where q_i represents the contribution of track i to the likelihood L_k:

$$q_i = \frac{\beta_N}{\beta_F} P_{TL_k}(TL_i)\, P_{DS_i} \prod_{j=1}^{NU_i} \frac{1}{\beta_F} f_i(\nu_{ij}) \tag{14}$$

Taking the logarithm of (13) and omitting the constant term, maximisation of L_k is strictly equivalent to maximisation of L'_k:

$$L'_k = \sum_{i=1}^{TN} \ln q_i \tag{15}$$

Now, we consider the set of all the possible tracks that can be constructed using the observations of the k latest scans; for each of them, we compute their likelihood q_i. The maximization of the partitioning likelihood is then equivalent to the search of the tracks that maximize J:

$$J = \sum_{i=1}^{TT} \ln q_i \tag{16}$$

where TT represents the number of all the possible tracks satisfying the constraint that a plot is assigned to at most one track. To each possible track i, we associate a binary vector ψ_i defined as:

$$\psi_i(j) = \begin{cases} 1 & \text{if plot } j \text{ is used by track } i \\ 0 & \text{otherwise} \end{cases} \quad , j = 1..NP \tag{17}$$

The constraint can be expressed as follows:

$$\sum_{i_1=1}^{TT} \sum_{\substack{i_2 = 1 \\ i_2 \neq i_1}}^{TT} \psi_{i_1}^t \psi_{i_2} \tag{18}$$

The maximization of the partitioning likelihood can then be reduced to the minimization of the following energy:

$$E = -\sum_{i=1}^{TT} \left[\frac{\ln q_i - m_q}{m_q} \right] + \frac{B}{2} \sum_{i_1=1}^{TT} \sum_{\substack{i_2 = 1 \\ i_2 \neq i_1}}^{TT} \psi_{i_1}^t \psi_{i_2} \tag{19}$$

where B is a positive factor which determines the relative influence of the constraint, and:

$$m_q = \min_i (\ln q_i) \tag{20}$$

This energy can be compared with the energy of the Hopfield neural network [13]:

$$E_H = -\sum_l I_l f(x_l) + \frac{1}{2}\sum_l \sum_m W_{lm} f(x_l) f(x_m) + \sum_l \int_0^{x_l} \varepsilon f'(\varepsilon)\, d\varepsilon \quad (21)$$

where x_l is the state of the l-*th* neuron, $f(x_l)$ is its output, and f is the sigmoid function:

$$f(x) = \frac{1}{1+e^{-px}} \quad (22)$$

p being a constant parameter. I_l is the input of the neuron l and W_{lm} is the weight of the connection between neuron l and neuron m. The neuron update rule that ensures the minimization of E_H is given by:

$$\frac{dx_l}{dt} = -x_l + I_l - \sum_m W_{lm} f(x_m) \quad (23)$$

The last term of equation (21) can be neglected for a sufficiently large value of p. Thus, we can define a neural network that minimizes (19) by identifying the weights and the inputs. We obtain:

$$I_l = \frac{\ln q_i - m_q}{m_q} \quad (24)$$

$$W_{ml} = B(1-\delta_{lm})\, \psi_l^t \psi_m \quad (25)$$

where δ_{lm} is the Kronecker symbol:

$$\delta_{lm} = \begin{cases} 1 & \text{if } l = m \\ 0 & \text{otherwise} \end{cases} \quad (26)$$

The neuron update rule (23) becomes:

$$\frac{dx_l}{dt} = -x_l + \frac{m_q - \ln q_l}{m_q} - B \sum_{\substack{m=1 \\ m \neq l}}^{TT} \psi_l^t \psi_m f(x_m) \quad (27)$$

4. SIMULATIONS RESULTS

In this paragraph, we present some simulation results to illustrate the behaviour of the proposed neural traching method. The performance of this method are compared with those obtained with two classical traching methods : the nearest neighbor (NN) method [11] and the Joint Probabilistic Data Association (JPDA) filter [15]. Figure 1 shows a scenario with nine simulated target trajectories. The corresponding plots were generated during 150 scans for a radar sensor characterized by measurement noises, with $120m$ of standard deviation in distance, $4mrd$ of standard deviation in azimuth, with a detection probability of 0.85 and a range of $150km$. To decrease the number of potential tracks to form, two gating techniques are applied. First, a plot j is associated to a track i only if [14]:

$$\nu_{ij}^t C_i^{-1} \nu_{ij} \leq \rho \quad (28)$$

where ρ is determined by means of a Chi-square table. Then, if assignment is accepted, and if the likelihood of the formed track is less than a pre-specified threshold, the track is deleted.

Figures 2, 3 and 4 show the tracking results using respectively the NN method, the JPDA Filter and the proposed neural solution.

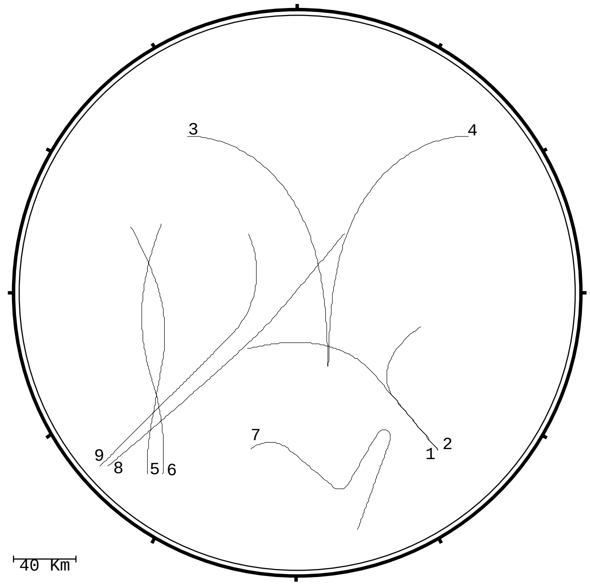

Figure 1: Simulated target trajectories.

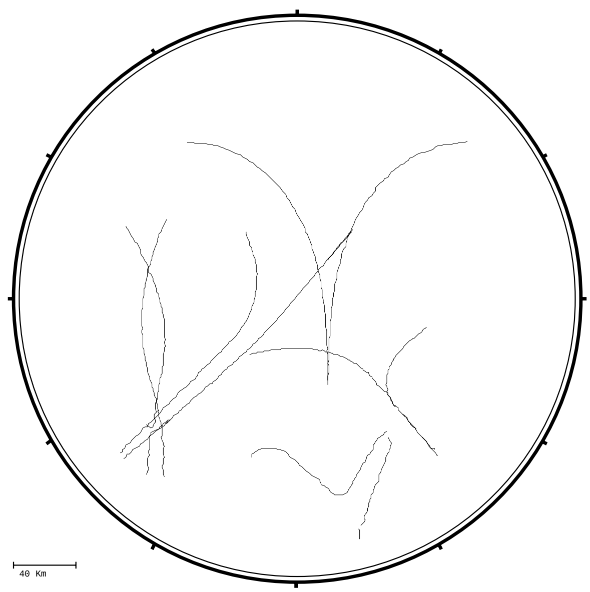

Figure 2: Tracking results using the Nearest-Neighbor method.

We can conclude that the JPDA Filter and the neural method allow to correctly track the targets $5, 6, 8$ and 9 when they are crossing, while the NN method mistakes the targets 5 and 8. We can also notice that the NN method decides incorrect associations for the targets 1 and 2 that are very close each other, which leads to several track breaks. The JPDA Filter also has some difficulties for tracking these targets: it can not distinguish that there are two separate targets, so it merges them.

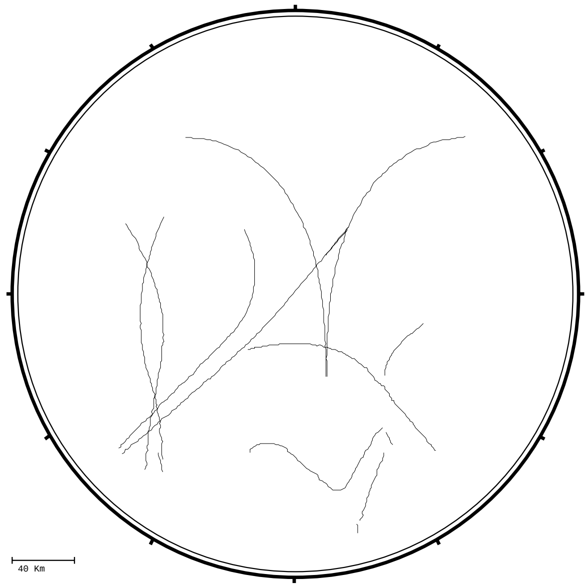

Figure 3: Tracking results using the JPDA Filter.

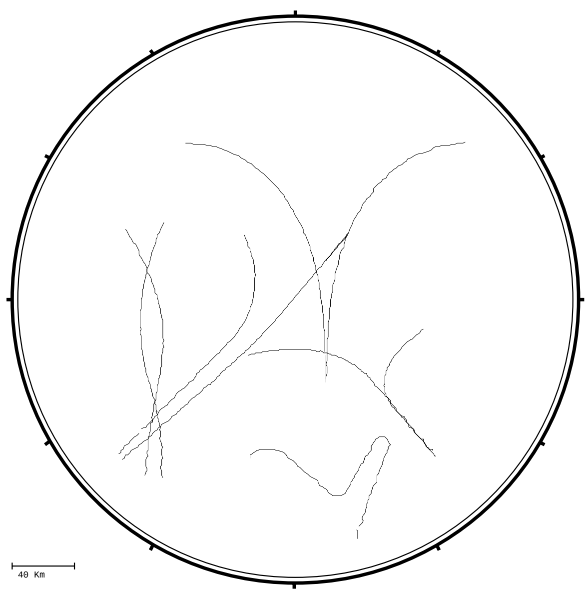

Figure 4: Tracking results using the new neural network based approach.

5. CONCLUSION

In this paper, we have described a new neural tracking method, based on the optimization of a likelihood function. We have shown that a neural network, that fastly converges to near optimal solutions, can solve such a combinatorial optimization problem.
Simulation results have been presented to illustrate the behaviour of the proposed tracking method and to compare it with two classical tracking methods (NN method and JPDA filter). The best tracking results were obtained with the neural method, specially when targets are crossing or close each other.
Finally, it is important to notice that the proposed method allows to simultaneously solve the track initiation and maintenance problems as a global optimization problem, which is not the case with classical traching methods.

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